Heart Diseases and Diabetes

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Abstract- **The aim of this study is to investigate whether changes in heart rate variability (HRV) signal in people with diabetes are at increased risk for cardiovascular disease (CVD). Diabetes is significant health problem and cardiovascular disease is the leading cause of diabetes-related death. Early detection of diabetes is an important factor to reducing the mortality. This study was well suited to the diagnosis of cardiac dysfunction, but here we used the same measures to detect diabetes. Using the wavelet-coefficient standard deviation of HRV signal, it was possible to discriminate diabetic patients from normal subjects. The perfect discrimination achieved in our study is at scale 5.**
Keywords– HRV, CVD.

I. INTRODUCTION

HRV expresses the variations of both instantaneous heart rate (IHR) and RR intervals (intervals between QRS complexes of ECG). PhysioBank contains many digitized ECGs that are already annotated beat-by-beat, so the exact time of QRS complex within the ECG has been recorded in a *beat annotation file*. Effective use of PhysioBank data requires specialized software and much of it is contained within the WFDB SoftwarePackage such as sqrs, wqrs, ecgpuwave, bxb, nguess and tach algorithms [1]. Sqrs,wqrs and ecgpuwave algorithms can be used to detect QRS complexes in order to extract the HRV from ECG records. The sqrs detected the QRS complexes and locating the peak [2], the wqrs detecting QRS onsets of the QRS complexes [3], and ecgpuwave detected the QRS complexes and locating the peak [4].

Autonomic nervous system (ANS) is the portion of the nervous system that regulates individual organ function not under voluntary control such as the heart. The two branches of the ANS, the vagal (PNS) and sympathetic (SNS); both play a role in modulating normal activity of the heart. Thus HRV is a noninvasive marker reflecting the activity of the PNS and SNS components of the ANS on the heart. Studies have summarized that cardiac response to PNS activity is rapid, while the response to SNS activity is slower characterized with a time delay [5]. So, HRV components tend to aggregate within several frequency bands. The frequency band range from about 0.15 Hz to 0.4 Hz is referred to as the high-frequency (HF) band and the frequency band range from about 0.05-0.15 Hz is referred to as the low-frequency (LF) band. The PNS activity is characterized by the HF band. The LF heart rate rhythms have been suggested to reflect mainly SNS outflow, but have also been thought to reflect both PNS and SNS activity. Diabetes is a chronic condition in which the body produces too little insulin or unable to use available insulin efficiently. Untreated, diabetes can cause long-term complications. Such as Hyperglycemia which is elevated glucose levels cause damage to nerve endings with the increased amounts of glucose in the peripheral nerves of human diabetics, leading to autonomic neuropathy and heart dysfunction. Around 75% of people with diabetes die from cardiovascular disease, including heart attack and stroke [6]. Studies of HRV have been demonstrated that the scale-dependent wavelet transform standard deviation of the HRV can be used to discriminate patients with certain forms of cardiac dysfunction from normal subjects [7, 8].

II. METHODOLOGY

The Fourier Transform (FT) is the most popular transform used to obtain the frequency spectrum of a signal. The FT tells how much of each frequency exists in the signal, but it does not tell at which time these frequency components occur. To solve this problem, the Short-Time Fourier Transform (STFT) was introduced. The major drawback of the STFT is that it uses a fixed window width. In contrast to STFT, which uses a single analysis window, the wavelet transform (WT) uses short windows at high frequencies and long windows at low frequencies. Thus, when the wavelet analyzes slow waves as the T wave, longer (high scale) wavelets are needed. And with rapid waves, like the QRS complex, shorter wavelets (low scale) are needed. WT is a useful technique for analyzing signals at multiple scales. WT permits the time and frequency characteristics of a signal to be simultaneously examined. There are many functions that can be used for WT such as haar, daubechies (dbN), and symlet (symN); see Fig. 1.

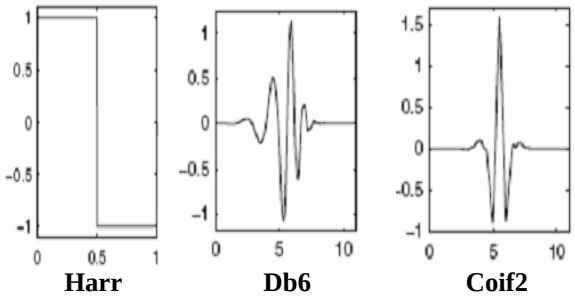

Fig. 1. Some types of different wavelet families.

The Continuous Wavelet Transform (CWT)

The signal to be analyzed is multiplied with a wavelet function just as it is multiplied with a window function in STFT, and then the transform is computed for each segment generated. However, unlike STFT, in WT, the width of the wavelet function changes with each spectral component. The WT, at high frequencies, gives good time resolution and poor frequency resolution, while at low frequencies; the WT gives good frequency resolution and poor time resolution.

B. The Discrete Wavelet Transform (DWT)

DWT is easy to implement and reduces the computation time. In CWT, the signals are analyzed using a set of basis functions which relate to each other by simple scaling and translation. In the case of DWT, a time-scale representation of the digital signal (X) is obtained using digital filtering techniques. The DWT decomposes the discrete time-domain signal by successive low pass filtering (LPF) and high pass filtering (HPF) of the X. An approximation (cA) vector is the low-frequency components of the signal, while a detail (cD) vector is the high-frequency components. These vectors are obtained by convolving X with LPF for cA and with HPF for cD. The decomposition process is continued with successive approximations being decomposed in turn until the desired level is reached; see Fig. 2.

Table 1
The results for the estimation of the performance of the 3-QRS methods on 3 records from Long Term Data Base. The wqrs algorithm have a slightly higher sensitivity.

Algorithm	**Sensitivity**		
	S20121	S20320	S20481
Sqrs	99.98	99.86	99.75
Wqrs	99.98	99.94	99.94
ecgpuwave	99.81	99.94	99.88

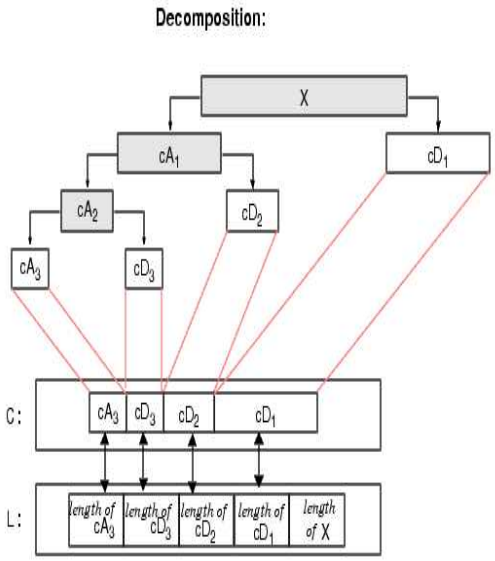

Fig. 2. 3-level wavelet decomposition of discrete time-domain signal (X).

III. RESULT

The 2-minute IHR recordings (12 normal patients and 14 diabetic patients) for the analysis and classification were obtained from the PhysioBank, exactly from PTB Diagnostic ECG Database [9]. The sampling frequency of the records was 1000 Hz. The WFDB was installed on Windows XP platform with MATLAB R13. Accurate determination of the QRS complex is essential in for a correct measurement of HRV. A small numbers of uncorrected QRS detection or classification errors can lead to wrong HRV analysis results. To estimate the performance of the available QRS detection algorithms in the WFDB, we tested and then compared its output with the reference annotation files using bxb algorithm. We corrected the out put of the QRS detection algorithm using nguess routine, because each QRS detector algorithm will miss some and mistakenly add some QRS complexes. The bxb algorithm compared two annotation files associated with the same record, one of these was the reference annotation file and the other was the test annotation file which was produced by one of the 3 QRS detection algorithms. Only 3 diabetic records with their reference annotation files were available from Long Term Data Base [10]. These records were 24-hour record. The results were presented in terms of sensitivity (Se), ratio of TP QRS detected over total of QRS. Se = TP/ (TP+FN).
TP (true positives = QRS detected).

Table 2
The results of the nguess on the 3-QRS routines, nguess is much more useful with wqrs.

Algorithm +Nguess	**Sensitivity**		
	S20121	S20321	S20481
sqrs	100.00	99.91	99.91
wqrs	100.00	99.94	99.96
ecgpuwave	99.83	99.94	99.89

FN (false negatives = missed QRS detection).
The nguess improved the out put of QRS detection alogorithms, it added the missing beats and eliminated the false detection. The estimation of the performance of QRS detection algorithms: sqrs, wqrs and ecgpuwave was done to choose a suitable QRS detection algorithm for extracting the HRV signal of the data set. The results are presented in term of Se see table 1 and table 2. DWT required a uniformly sampled instantaneous heart rate signal, an evenly-spaced IHR signals were obtained using tach routine. The IHR sequences were projected into a wavelet space to obtained wavelet coefficients using DWT. The standard deviation (sigma) of wavelet coefficients at each scale was used to discriminate between healthy and diabetic patients. The principal results of this research are displayed in Fig. 3, where sigma is plotted vs. scales ($1 \leq m \leq 7$) for all patients, using the db1 wavelet; normal patients indicated by open squares and diabetic patients indicated by filled circles. At scale 5, sigma serves to completely separate the two classes of patients.

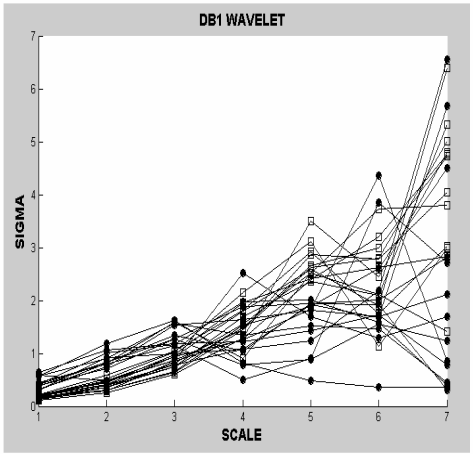

Fig. 3. Wavelet-coefficient standard deviation (sigma) versus scale m for the 26 data set collection using db1 wavelet.

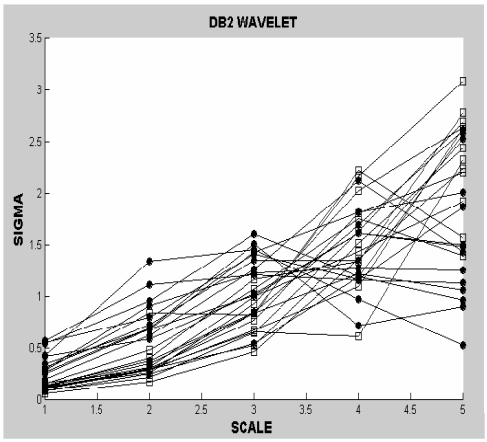

Fig. 4. Wavelet-coefficient standard deviation (sigma) versus scale m for the 26 data set collection using db2 wavelet.

The depression of Wavelet-coefficient standard deviation at scale 5 is likely associated with the impairment of ANS function thereby providing a clinically significant measure of the presence of heart failure. But at smaller, and at larger scales, there are multiple overlaps of the diabetes and the normal individuals. We calculated the sigma for many wavelet families and for most of them there is complete overlap between normal and diabetic subjects at all scales as it was evident in Fig. 4.

IV. Discussion

Wqrs is selected to extract HRV signal for many reasons, firstly wqrs gives the onset of QRS for an arrival of a beat. The others two give a point somewhere within the QRS (usually at around the largest slope of the QRS waveform), Such point would fluctuate with change of QRS morphology that may introduce an error in HRV analysis. Secondly wqrs has a slightly higher Se as shown in table1. Lastly, it is clear from table 2 that nguess is much more useful with wqrs since it is able to produce maximum improvement.
Scale-dependent statistics are constructed by transforming the discrete-time sequence of IHR into a space of wavelet coefficients. The coefficients are obtained by carrying out the DWT. We present results for db1 which gives 7 levels of decomposition; similar results are obtained using other wavelets give 7 levels for our signal such as harr, and sym1. But for wavelet families gives less

than 7 levels such as db2, or sym2 there is no separation between diabetic and healthy patients at any scale. So for short IHR signal we have to use compact version of wavelet families rather than dilated ones.

The wavelet coefficients for the diabetic patient evidently exhibit substantially reduced variability, particularly at scale 5. The measure for this variability is sigma as a function of scale. At scales 5, sigma serves to completely separate the two classes of patients, thereby providing a clinically significant measure of the presence of diabetes. But at smaller, and at larger scales, there are multiple overlaps of the diabetes and the normal. The results indicate that healthy patients exhibit greater fluctuations than those afflicted with diabetes at scale 5. The modulations of the sympathetic and parasympathetic tone lie in the range 0.04 to 0.15 Hz which is the frequency range of scale 5. So we emphasize the impact of the diabetes on the ANS. The results indicate that the HRV alone suffice as a measure for the presence of heart dysfunction and diabetes; the full ECG in not required. The results indicate that HRV analysis can be based on short IHR data (2 minute), rather than 24-hours recordings.

V. Conclusion

HRV analysis enabled us to correctly classify every patient in data set as either belonging to the diabetes or normal group, thereby providing a clinically significant measure of the presence of heart-failure in diabetes patients. HRV testing provides early detection and thereby promotes timely diagnostic and therapeutic interventions.

Early detection of autonomic dysfunction can encourage patient and physician to improve metabolic control and to use therapies such as to be physically active, if you are overweight, try to lose weight, manage high blood pressure, manage hyperglycemia and manage dyslipidaemia.

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